Early Detection and Classification of Rice Disease using Hybrid Deep Learning Technique

SHORT SYNOPSIS

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DOCTOR OF PHILOSOPHY

by

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DECLARATION BY THE SCHOLAR

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It is the work that is expected to be carried out under the supervision of **Dr. Urmila Pilania**.

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ABSTRACT

Productivity in rice is impacted by various and highly contagious diseases, resulting in a significant loss of yield. Conventional methods for rice leaf disease detection and classification are based on human expert evaluation, which is prone to human error and variability based on the evaluator's experience, growth stage of the rice plant, and environmental factors. Although recent developments in machine learning and deep learning, especially CNN-based models, have improved the accuracy of automated disease classification, the lack of adoption of advanced models like Faster R-CNN and vision transformers has hampered classification accuracy, often resulting in a higher rate of misclassification.

To address these challenges, this study proposes a hybrid deep learning model that integrates CNN-based feature extraction/RCNN/fast CNN, attention mechanism and transformer models for early and accurate rice disease classification. The proposed method is expected to improve the accuracy of classification and minimize the rate of false classification. The performance of the proposed model will be assessed using accuracy, precision, recall, F1-score and other standard metrics.

Keywords: Rice Disease, Computer Vision, Deep Learning (DL), Machine Learning (ML), Convolutional Neural Networks, Attention Mechanism, Transformers.

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INTRODUCTION

India is an agricultural country with a history of rice cultivation exceeding 7,000 years. It has great importance in the Indian agricultural sector as crop (Kharif). Its production is concentrated in the key humid and tropical states like Punjab (PB), Uttar Pradesh (UP), Andhra Pradesh (AP), Bihar (BH), Odisha (OD), Chhattisgarh (CHG) and West Bengal (WB). Rice has harvested area of 651,936 hectares in 2022 and an average yield of 2.7 to 2.8 tones/hectare [1][2]. The problems affecting rice production are varied, with the most relevant being the rising cost of agricultural inputs, low market prices, and phytosanitary issues that occur at various phonological stages of different cultivars [3][4][5]. The above states have ideal soil and climate characteristics for rice production. However, these soil and climate characteristics, combined with the low quality of the genetic material planted in the country, the use of recycled seeds, and incorrect use of pesticides. These factors have contributed to an increase in fungal, bacterial, and viral diseases [6].

Chemical control is the most commonly used management method for phytosanitary problems of fungal, bacterial, and viral origin. Chemical control is prioritized because there is accessibility to acquire the products, ease of use of the inputs in the field, and their effectiveness. In order to ensure the reduction of the incidence and severity of fungal, bacterial, and viral diseases, it is very important to use active ingredients selectively and in a targeted manner based on the characteristics of the pathogen. In the trial area, there is a high incidence of pathogens of fungal origin, the most prevalent being Rhizoctonia, Pyricularia, Sarocladium, and Helminthosporium, among other microorganisms associated with the grain spot complex. These pathogens affect yield because they cause spotting, reduce germination, vigor, seedling size, number of grains per panicle, grain weight, and grain filling [6].

- **Rice Plants**

Rice plants are special plants because they can adapt to almost all environments, from lowlands to highlands (2000 m above sea level), from tropical to subtropical except Antarctica (polar regions), from humid areas to dry areas, and fertile fringe areas (stress salt, aluminum, iron, organic acids, drought, etc.). Rice plants are a type of grass with strong bunches and many shoots growing from rooted segments. According to where they grow, rice plants can be divided into paddy rice, dry land rice, and swamp rice. The wetland rice farming system was

known before the dryland rice farming. Rice cultivation in the wetland system has existed since 6280 BC it is known that the dry land system was only known around 2000 BC [10][11][12]. The rice cultivation system was first developed in China, while the rice system was first identified on the Korean peninsula. In India, the dry land rice cultivation system developed earlier than the wetland rice cultivation system. This refers to the cultural patterns of our ancestors who lived a nomadic (moving) life. So, when agricultural land fertility decreased, they opened new land to cultivate various crops, including dry land rice [13] [14]. People are familiar with thousands of rice plants in nature, but not all of them have economic value.

Rice plants have one leaf. The leaf sheath is well developed, often with tongues on the edge of the leaf sheath and leaf blade. The leaf stalk is sessile, almost always lanceolate or striated on both sides of the sheath, with several parallel veins. The leaf surface is rough and narrows at the tip. The length of the leaf blade varies greatly, mostly 100-150 cm. The color of the leaves is dark green and changes to golden yellow after the crop is harvested. Rice disease is a biotic stress that can reduce yields and even cause crop failure. The following are the types of rice leaf diseases:

- *Brown Spot*: Narrow brown spot disease in rice is caused by a fungus, Cercospora oryzae, and short lines of light brown, slightly reddish spots that extend to the veins of the plant's leaves are susceptible to serious infections [15].

Figure 1: Brown Spot disease [15]

These necrotic spots or brown spots occur on mature plants, appearing as brown circular patches with gray to white centers and reddish edges. This disease could cause leaf damage and reduce yields, as represented in Figure 1.

- *Leaf Scald*: Leaf scald or rice leaf blister is a disease caused by the bacteria Xanthomonas oryzae pv. Oryzae symptoms of this disease include mild water-soaked lesions on the leaves, starting at the leaf tips [16].

Figure 2: Leaf Scald Disease [16]

The Leaf Scald lesions then widen and form blisters on the leaf blades. Infected leaves then wilt. This disease usually occurs at the tips of older leaves, but can also occur along the edges and center of the leaves, as shown in Figure 2.

- *Narrow Brown Spot*: Narrow brown spots on rice leaves are a disease caused by the fungus Cochliobolus miyabeanus. Symptoms of this disease are the presence of round or oval brown spots with a yellow halo at the pillaring stage [17].

Figure 3: Leaf Scald Disease [17]

As the spots enlarge, a gray center appears in the center and a reddish-brown border is visible. Stem discoloration can also be another characteristic symptom. Infection of the florets causes incomplete or disturbed grain filling and reduces grain quality, the plant with diseases is as illustrated in Figure 3.

- *Disease Blast caused by fungus Pyricularia oryzae*: This disease infects the leaves, neck of the panicle, stems of rice, and can cause a decrease in rice yields. In the vegetative phase, early symptoms of the disease; Blast look like a colored diamond-shaped patch, brown with a white dot in the center. If not controlled properly, this disease could spread to damage the neck of the panicle, resulting in the stalk, panicles break, and the grain becomes empty as shown in Figure 4.

Figure 4: Disease Blast [17]

This disease spreads the fungus, which is greatly influenced by high humidity conditions, as well as temperatures that support growth. Hence, it is important to choose rice varieties that are resistant to the disease Blast and carry out crop rotation to break the cycle of the fungus that causes it to live [17].

- *Disease Blight (Crackling):* In rice plants it is caused by bacteria Xanthomonas oryzae. This bacterium attacks the leaves of rice plants, which causes symptoms such as the appearance of yellow lines until the leaves turn brown represented in Figure 5. In advanced stages, the leaves will dry out and die. The spread of this disease can occur very quickly, especially in humid environments and high temperatures [18].

Figure 5: Disease Blight [18]

This disease is very detrimental because it can reduce the harvest yield significantly, especially at the generative stage when the plant starts to flower. The bacteria that cause Blight can infect plants through wounds on the leaves, generally caused by wind or rain that carries the bacteria.

- *Disease Tungroin*: Rice plants could be double infection of two types of viruses: Rice Tungro Spherical Virus (RTSV) and Rice Tungro Bacilliform Virus (RTBV). This disease is transmitted by a vector in the form of a green leafhopper (Nephotettix virescens), which spreads viruses by sucking plant fluids.

Figure 6: Disease Tungro [19]

Symptoms of the disease Tungro include changes in leaf color to orange-yellow, which starts from the tip of the leaf and then spreads to all parts of the leaf as shown in Figure 6. In addition, infected plants will experience stunting and stunted shoots. In the advanced stage, rice plants infected with this virus will grow very slowly and ultimately produce empty grain [19].

The involvement of agricultural expert's increases agricultural production. Diagnosing rice plant diseases through optical observation of leaf symptoms is quite complex. Rice leaf diseases create significant pressure to food protection, but early discovery remains intricate in some parts of India due to limited infrastructure. Therefore, accessible, low-cost technology needs to be developed to ensure equitable access to plant disease information. With the widespread availability of digital cameras and advances in the field of computer vision, automation models for high-precision diagnosis in the agricultural sector are urgently needed, such as for plant phenotyping, smart greenhouses, and so on.

DL is the most broadly used technique and it has applications in several fields. DL is actually a subfield of ML, which was initially inspired by the structure of the human brain. ML is a computer program that can learn from experiences. In practice, the ML models won't improve significantly beyond a certain point, regardless of the amount of data given to it for training the models. Therefore, deep learning was developed to address the performance issues of traditional machine learning algorithms as data grows. Deep learning has several algorithms which could be used in the field of computer vision.

One of the most well-known algorithms for image processing is CNN, although several other algorithms have been used in previous research. A similar study on rice plant diseases was conducted by [7], who focused on blast disease and used the algorithm named Local Binary Pattern and Histogram. Researchers focused on differentiating rice plants infected with blast disease from those not infected. Other research also discussed rice diseases, including rice blast disease and smut, using an algorithm Faster R-CNN to distinguish whether rice is infected with smuts or not. However, the research conducted by [8] depicted that it cannot yet be fully stated as object detection, because it only differentiates whether the rice plants are suffering from false smut or not. This research tends to be more binary classification with the addition of localization. Furthermore, research conducted by [9] used FCM-KM and Faster R-CNN to identify three types of diseases in rice plants, namely blight, bacterial blight, and blast, with an accuracy 96.71%, but there are still some things that can be done for improvement. While the

research model can only identify one type of disease in a single rice plant, the reality in the field is likely be different. For example, rice plants may be suffering from more than one disease simultaneously, while if the model can only identify one disease in a single plant, the information obtained is not optimal to support the hypothesis that rice can suffer from more than one disease simultaneously.

LITERATURE REVIEW

The performance of CNN was compared with the models VGG16, Inception V3, MobileNetV2, NasNet Mobile, SqueezeNet, and SimpleCNN in paper [20]. The data used was taken directly, with a total of 1426 images and 9 classes. The accuracy results obtained were 97.12% for VGG16, 96.37% for Inception V3, 96.12% for MobileNetV2, 96.95% for NasNet Mobile, 92.5% for SqueezeNet, and 94.33% for SimpleCNN. The International Rice Research Institute (IRRI) and Bangladesh Rice Research Institute (BRRI) dataset with a total of 323 images having 5 classes, namely Blast, Bacterial Leaf Blight, Brown Spot, Sheath Blight, and Tungro were utilized in work [21]. Then, utilizing CNN and augmentation methods authors obtained the maximum accuracy results of 99.78% and 97.35%, respectively, for training and testing.

Dataset is taken from Dharmsinh Desai University in Gujarat, India. It carries 120 JPG images and 3 classes of diseases. The images were labeled and divided into a training set consisting of 56 images and a test set consisting of 24 images. Artificial Neural Network (ANN) model was trained in Google Colab with 100 epochs, achieved 83% accuracy, 84% precision, recall 84%, and F1-score of 83%, which demonstrates a robust system for automatic diagnosis of rice diseases [22].

The study conducted by [23] involved collecting a dataset of images representing various rice leaf diseases, such as tungro, blast, leaf blight, brown spot, and leaf rot diseases. Image resized to 224 × 224 pixels and normalized to [0, 1]. To assess the effectiveness of the model, the dataset was divided into training 80%, validation 10%, and testing 10%. The CNN has a low loss rate and low over fitting, with an accuracy of 0.914.

Researchers in [24] shown that rice diseases are one of the biggest factors affecting rice yield. In the past, manual identification was time-consuming and laborious. Therefore, it is necessary and inevitable to realize automatic identification of rice diseases. In terms of rice disease identification, they used colorimetric models, edge extraction, and morphological methods to identify leaf blast, and the final prediction accuracy was 90.03%.

Researchers in [25] proposed an automated classifier for pest recognition and classification based on a combination of saliency methods and CNNs. By using saliency methods, the study created new labeled samples, enhancing image data by discarding low-importance pixels, and

trained multiple networks using these new samples to build an ensemble model, achieving 92.43% accuracy on a small dataset and 61.93% accuracy on the IP102 dataset. Researchers in [26] proposed a diagnostic system based on transfer learning for pest detection and recognition, which achieved an accuracy of 93.84% by testing ten types of pests. Other studies use a model attention-based neural network optimized with Bayesian techniques, which achieved an accuracy of 94.65% on 2,370 rice leaf samples [27].

Li et al. [28] used traditional image processing, and convolutional neural networks method to identify rice false smut. Based on this, neural networks were utilized to classify six kinds of rice diseases, and good results were obtained. Researchers used the CNN technique and achieved the precision 97.96%, recall 98.19%, and the accuracy 97.64%.

Researchers in [29] conducted a similar study; they used a rice plant disease diagnosis method for three common rice diseases: Brown Spot, Leaf Blast, and Bacterial Leaf Blight. This technique attempts to separate diseased parts using the K-Means clustering technique. Color, texture, and shape characteristics were retrieved from diseased rice plant parts. Rice diseases were identified using an SVM classifier based on disease stage. This technique achieved an 90.95% accuracy for Brown Spot, 95.09% Leaf Blast, and 86.81% Bacterial Leaf Blight.

Researchers in [30] illustrate that the proficiency of CNNs has established elevated efficacy in rice plant disease categorization. A CNN method qualified on the dataset by the PlantVillage repository accomplish 99.64 % accuracy throughout training, highlighting the network's well-built power in challenging circumstances. Afterward, [31] developed an additional proficient DL model which promotes enhanced results, with new attained accuracy more than 98% on dissimilar leaf syndrome datasets. Furthermore [32], a hybrid mechanism that merges CNN with LBP attained the precision 99%.

Researchers in [33] showed that cultivation and farming is a foremost provider for living in Bangladesh, and premature rice infection recognition is essential for curtail acquiesce and crop failure. They utilized CNN with a ViT hybrid model for rice illness categorization with the dataset, namely Dhan-Shomadhan, and evaluated their performance with a conventional SVM. Investigational outcome illustrates that ResNet50 achieves better accuracy of 68.45%, a recall 61.1%, a precision 58.2%, and an F1-score of 59.89%.

Researchers in [34] concluded that the EfficientNetB5 & B6 attained exceptional accuracy for the overall test outcome with 99.05% and 99.27%. In [35], the accuracy of EfficientNetB5 is

higher than GoogleNet, ResNets, DenseNets, AlexNet, VGGNet, and MobileNets, with an accuracy accomplishing with 99.997%. Researchers in [36] depicted that DenseNet121 achieved the best performance, with 85.08% accuracy and F1-score while requiring only 8.1M parameters, making it suitable for deployment in resource-constrained agricultural environments for rice leaf disease detection.

Researchers in [37] showed that rice diseases cause substantial yield losses, creating a need for fast and automated diagnosis methods. This work proposed a hybrid deep learning model which retrieved features utilizing pre-trained CNNs (MobileNetV2, DarkNet19, and ResNet18) and performs classification using SVM. The proposed system achieved 98.61% accuracy, 98.85% specificity, and 97.25% sensitivity under 10-fold cross-validation, demonstrating its efficiency and reliability for rice leaf disease identification.

Machine Learning (ML)

One of the main branches of AI today is ML, also known as automatic learning. ML focuses on providing computers with the ability to learn on their own without needing to be told the rules they must follow to achieve their task. ML is categorized into three major types as follows in Figure 7 [38-41]:

- *Supervised learning*: It works on labeled data. It is the most popular technique for learning classifications and regression. This specifically refers for delivering the training data with a label that specifies the characteristics of the element for which the network is trained. The desired solution is included to help the algorithms correctly, value the data and assign an output value.
- *Unsupervised learning*: Focuses on letting the algorithm find variants of patterns and correlations. so, knowledge is only generated by finding similarities or characteristics in the input data. It can be considered the opposite of supervised learning because label information is not provided, and what is wanted to be achieved.
- *Reinforcement learning*: It is based on trial and error. The aim is to obtain a sequence of actions by the machine to achieve a certain task. The machine learns through a process of trial and error by reconfiguring internally to achieve the goal [41].

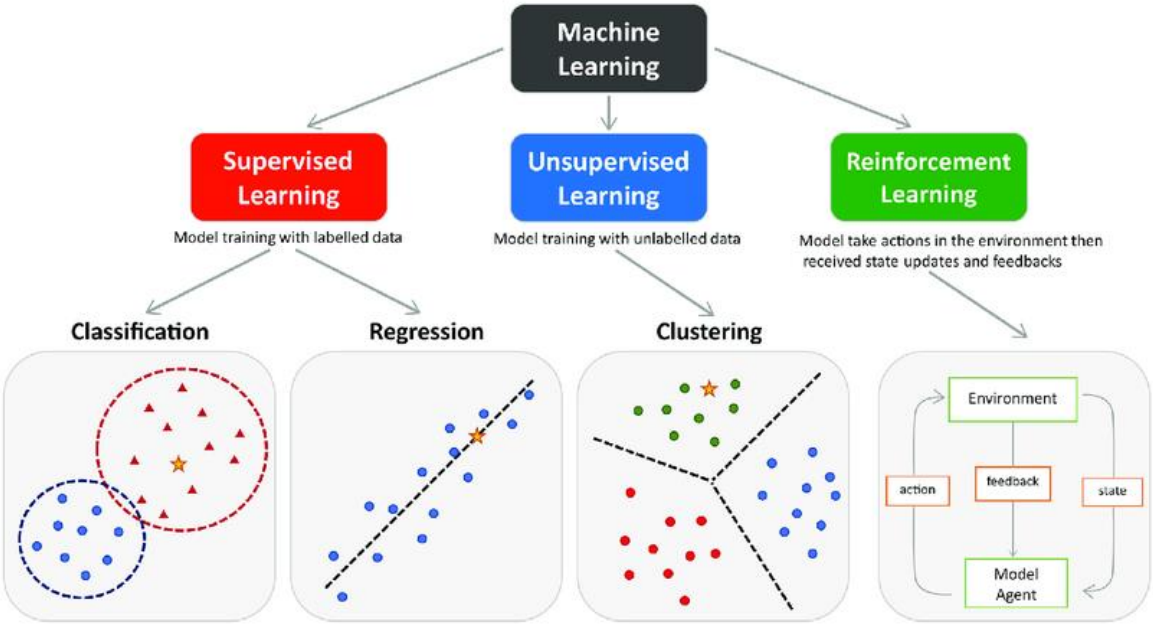


Figure 7: Machine Learning Model [39]

COMPUTER VISION

Computer vision, in recent years, has expanded into different fields of obtaining information, from the simplest, such as raw data extraction, to image patterns capable of being understood and interpreted. A very important role that complies with computer vision related to the field of AI is to obtain description information for the objects that you analyze from the feature extraction. The images are modified through computational processing, such as adjustment of sharpness, contrast, brightness, etc. It can be determined that computer vision works using algorithms and rely on optical sensors to extract information from the analyzed object [41]. This feature has allowed computer vision to overcome other techniques. Computer vision processes can be divided mainly into 3 activities:

- Obtaining digital images.
- The use of techniques for the processing and modification of images.
- The analysis and explanation of images for the use of their results in disease detection and monitoring of patterns.

Deep Learning (DL)

DL is a subset of ML and AI. According to [40][41], it is a technique for reducing high-dimensional data that uses hierarchical layers of hidden features to build predictors. Another

characteristic of DL model is pre-training, which comprises of settling the weights of every input value to values balanced in such a way as to avoid using small weights. So, that processing does not become extremely demanding. On the other side large weights do not create outcome which is deceptively optimal.

Convolutional Neural Networks (CNN)

The name CNN comes from the use of a mathematical operation called convolution and they are a specialized type of DL model that is consisting of layers. The layers process the signal in case of two-dimensional images, kernel detects different characteristics of the input image, resulting in an output [41][42]. Figure 8 illustrating part of a CNN convolutional layer and pooling layer with rectangular receptive fields. Multiple pairs can be used for successive layers. The above ideas are introduced to convolutional neural networks through three mechanisms:

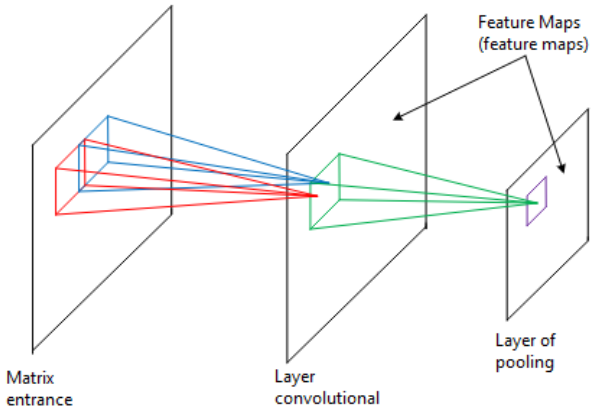


Figure 8: Layers of CNN Model

- *Receptive field:* In convolutional networks, every neuron is associated only to a local distinct region of the input volume, also known as receptive field. Receptive field can be described by its central location and size (kernel size). However, not all samples in a receptive field are equally important for their corresponding characteristic, since it depends on the set of network weights.
- *Filters:* Convolution operations are performed using filters or kernels. They are not previously defined but are learned during the training process. Thus, the filter weights will be the trainable parameters in a convolutional layer. In convolutional networks, multiple filters are utilized to retrieve different features from the input; their size or kernel size must match that of the receptive field.

- *Distribution of weights or Weight sharing:* Given the general assumption that the input is to be the procedure by the association can be partitioned into a set of confined sections with the same environment as described in the initial point every one of them can progress with the identical set of revolution that is with the same filters. With the previous postulation, we might decrease the count of parameters in the network balance to a fully connected network and enhance its generalizability.

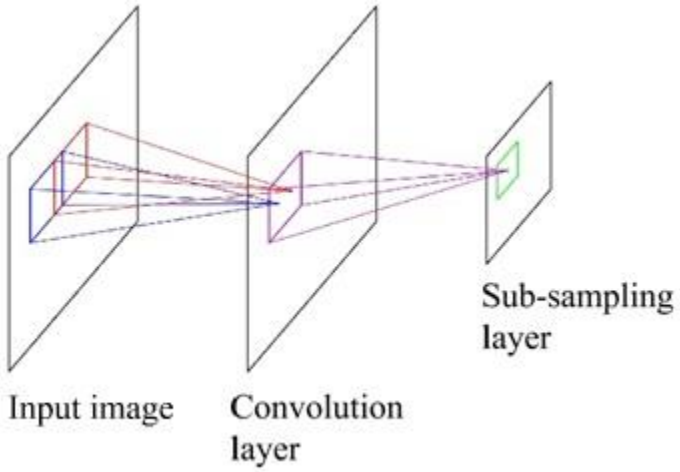


Figure 9: Example of Pooling [42].

- *Subsampling or pooling:* The subsampling or pooling operation reduces the dimensionality of retrieved feature maps as depicted in Figure 9. To do this, apply a window of an arbitrary size, and you can extract the sum of the windows, the maximum, or the average, depending on the specification of the user. Thus, this technique helps us minimizing the dimensionality in same time. Figure 10, shows a diagram of part of a convolutional network formed by an input matrix, a convolutional layer and a pooling layer.

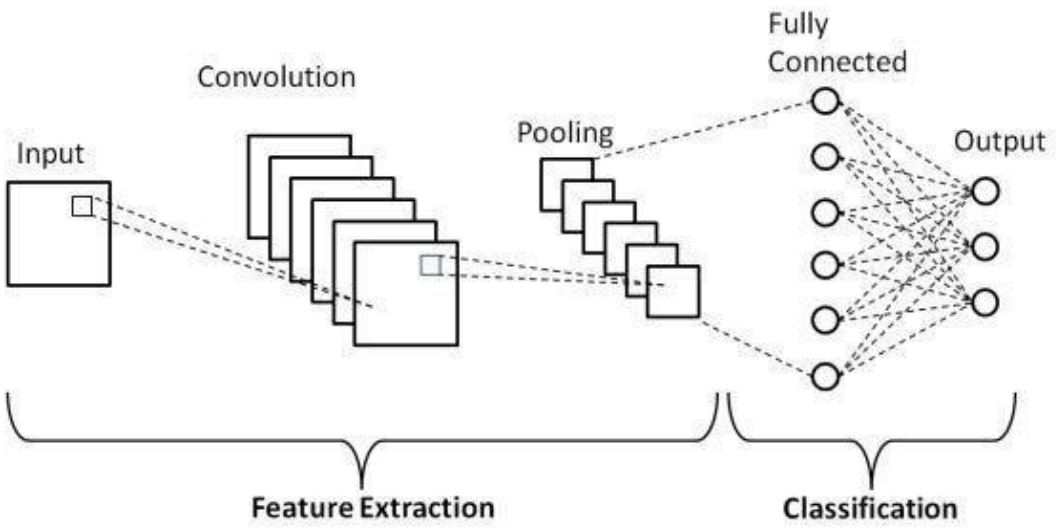


Figure 10: CNN Architecture [41]

- *Classification layer*: The classification layer is usually found at the end of the CNN structure. All the artificial neurons are connected just as in traditional neural networks in order to classify the data obtained through convolutions and parameter reductions. This top layer is fully connected to one output unit /class label, which depending on the count of labels in the classification will be the count of neurons used in the last layer of the network.

Transfer Learning (TL)

In recent years, the transfer learning technique has become very popular due to the great ability to save resources and efforts to get the best results when it comes to detecting objects in images. With other architectures, such as CNN, model would have to be trained from scratch that detects a particular object because there is simply no antecedent to have performed before, including adjustments or tests to achieve the best possible precision, so this process would require a lot of time and computational resources that have already been explained in the previous architecture. With TL, it is possible to create vision models computational for new objects never before detected from other existing models and pre-trained, it would only be enough to make minimal adjustments to be able to reach the required precision. Learning transfer consists of reusing a model that contains information (images) very similar to the object to be identified.

Faster Region-Based CNN (RCNN)

Faster-RCNN is born from the modification of pre-existing networks as shown in Figure 11. In this case, we can start from the RCNN, a neural network that extracts about 2000 Regions of Interest (ROI) and analyzes them separately in order to classify them [43].

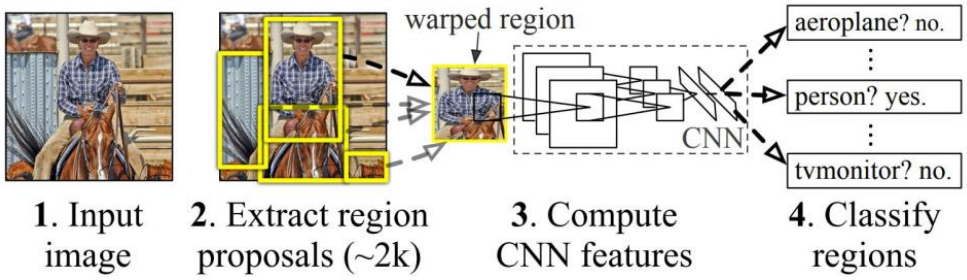


Figure 11: Architecture of an RCNN [42]

The biggest problem with this network is that the prediction for each new image takes between 40 and 50 seconds, implying that using large databases to train it involves adequate time.

The possibility of collecting all the ROI in a pooling layer could then be considered, where they are given a common size before entering the classifier. Thus, Fast-RCNN was born and represented by Figure 12.

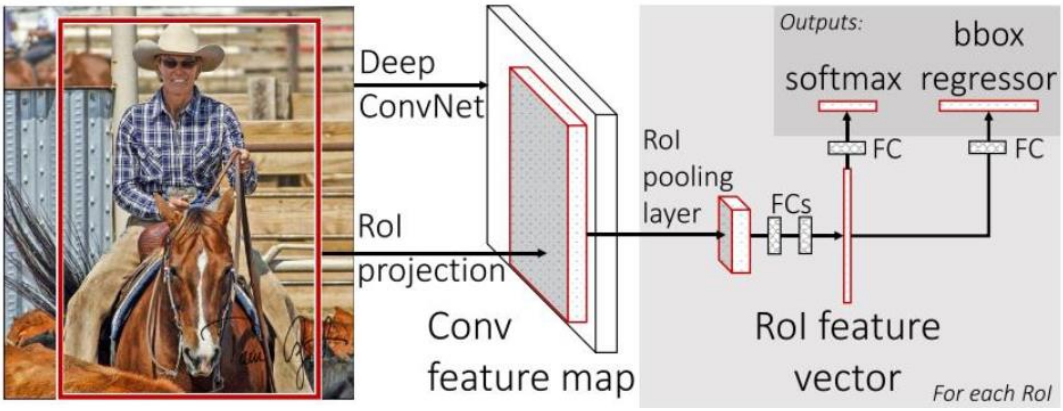


Figure 12: Architecture of a Fast-RCNN [42]

The advantage provided by Fast-RCNN comes from the added pooling layer, since this allows computing the 2000 regions simultaneously instead of sequentially. It takes very less time compared to RCNN; it takes 2 seconds it takes to single image classification.

Visual Transformers (ViT)

In order to correctly understand the operation of ViT, it is essential to recognize the operation of its main element, transformer. This type of architecture was developed to improve the limitations that the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) units presented when taking into account the temporal relationship between the different variables [43]. The differentiating element of transformer is found in its architecture, created to get rid of the recurring systems that the previously mentioned models made use of. To do this, they used self-attention mechanisms. Figure13 shows transformer architecture distinguish two main parts in its architecture: the decoder on the left side and the encoder on the right side. The encoder is the one in charge of taking the input and generating from it an intermediate representation that will later be decoded by the decoder. This, in turn, it will be responsible for generating the corresponding output [43].

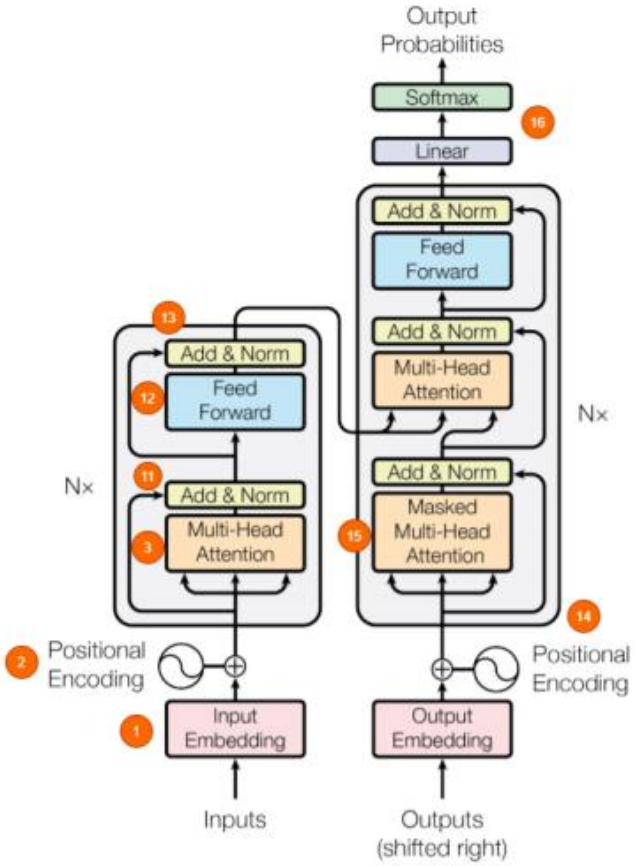


Figure 13: Architecture of a Transformer [43]

Explaining this process in greater detail, the input data is integrated into a vector to the superimposed layer or embedding layer, allowing a vector representation to be obtained for

each unit of information [44]. In the next stage, a positional encoding is performed to represent the order of the sequence. Multi-headed attention mechanism process is shown in Figure 14. Three vectors (query, key, and value) are generated for each of the input vectors. From query and key, a score matrix is obtained that represents the relationship for each unit of information. Higher the score, the greater the relationship and vice versa. This scoring matrix is subsequently reduced to the dimensions of query and key in order to ensure the stability of the gradients [43].

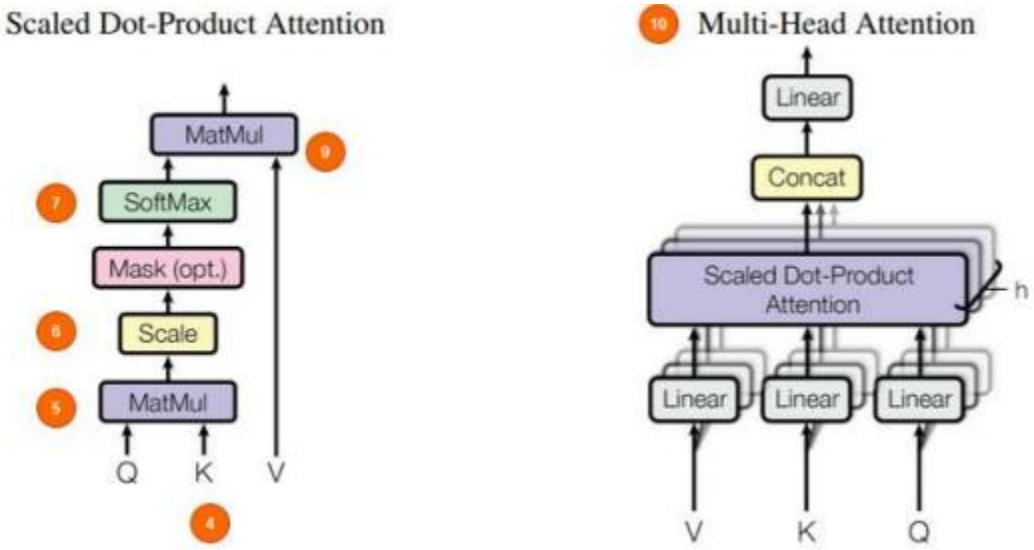


Figure 14: Multi-headed-attention architecture [43]

In the next stage of the process, the score matrix is subjected to a softmaxing process to convert the attention scores into probabilities. Softmax is used to get the attention weights.

Weights= $softmax(a) = where\ b_i = \frac{\exp(a_i)}{\sum_j \exp(a_i)}, b = [b_i, \ldots\ldots, n_n]^T$.The sum is weighted to obtain the output weight so $= \sum_{i=1}^{n} b_i v_i$. The most common are multiplicative attention and attention with a multilayer perceptron. With this mechanism, both keys and queries are projected in R^h using learned weights. The weights to learn are assumed to be $\alpha(q,k) = v^T \tanh W_k$. The resulting matrix is multiplied by the value vector, making the highest probabilities more important and those with lower scores considered irrelevant. This entire process is explained in detail in the Scaled Dot-Product Attention, whose inculcated output of the query, key, and value vectors passes through a linear layer for subsequent processing. Scaled dot product attention consists of query and key dimensions. D_k, and value dimensionD_v.

To calculate the scaled dot product, the query is multiplied by all keys and divided by $\sqrt{D}_k$ and apply the softmax utility to get the credence on the value.

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{D}_k}\right) \quad (1)$$

The self-attention mechanism is applied to each element considered as a unit of information by the network, in such a way that, as they are independent of each other, a copy of the self-attention module is used to process everything simultaneously (multi-headed). This is a collection of scalable dot-product functions attention, which allows the technique to simultaneously pay attention to data from various representations at different locations as shown in Equation 1.

$$MultiHead(Q, K, V) = Concat(head_1, \ldots., head_h)W^o \quad (2)$$

$$head_1 = Attention(QW^Q, KW^k, VW^v) \quad (3)$$

Finally, the output obtained passes through a feed-forward network, that is, a perceptron in which the connections between the neurons are unidirectional, to obtain a better representation. The outputs are normalized again, and the residues of the previous layer are added in this way to the output of the encoder, along with the inputs. From the previous steps, they pass to the decoder, where they follow a mechanism very similar to that described for the encoder to give the corresponding output probabilities for each of the initial inputs as a final result [43]. The Equation 2 and 3 represents complete process. Table 1 represents the research gaps which authors find after literature survey.

Table 1: Research Gaps

Research Paper	Dataset Used	Technique Used	Results	Research Gap
[24]	Field-acquired Rice Leaf Image Dataset	CNN-based real-time classification	Accuracy ≈ 91–94%	Lack of large-scale validation and early-stage disease analysis
[25]	Insect Pest Image Dataset	Bio-inspired features + ML classifiers	Accuracy ≈ 88–92%	No end-to-end deep learning; limited robustness to complex backgrounds
[26]	IP102 + Custom Pest Dataset	Transfer learning using CNNs	Accuracy ≈ 93–95%; Precision/Recall > 90%	Generalization and explain ability were not addressed
[27]	Rice Leaf Disease Dataset (public + private)	Attention-based CNN + Bayesian optimization	Accuracy ≈ 96%; F1 ≈ 0.95; AUC ≈ 0.97	Performance degrades under noise; no cross-dataset evaluation

[28]	Rice Pest and Disease Dataset	Two-level lightweight CNN	Accuracy ≈ 90–92%; Recall ≈ 89%	Weak fine-grained and multi-scale feature learning
[29]	Kaggle Rice Leaf Disease Dataset	Pre-trained CNN feature extraction	Accuracy ≈ 94%; Precision ≈ 93%; Recall ≈ 92%	No end-to-end learning or interpretability
[30]	Multi-crop Plant Leaf Disease Dataset	Deep CNN	Accuracy ≈ 92–95%; F1 ≈ 0.93	Class imbalance and domain shift were not resolved
[31]	Leaf Disease Image Dataset	Efficient deep learning architectures	Accuracy ≈ 93–96%	Edge/mobile deployment feasibility not evaluated
[32]	Plant Leaf Image Dataset	CNN + Local Binary Pattern (LBP)	Accuracy ≈ 95%; Precision ≈ 94%; Recall ≈ 93%	Increased complexity and over fitting risk
[33]	Multiple Rice Leaf Disease Datasets	CNN vs Transformer vs ML	CNN: 95–97%; Transformer: 93–95%	Transformers were not optimized for small datasets
[34]	Fruit Plant Disease Dataset (29 classes)	EfficientNet-B5/B6	Accuracy ≈ 97–98%; F1 ≈ 0.97	Heavy models are unsuitable for edge devices
[35]	PlantVillage Dataset	EfficientNet variants	Accuracy up to 99%	Clean dataset; lacks real-field validation
[36]	Benchmark Rice Disease Dataset	Five CNN models benchmark	Best Accuracy ≈ 96–97%; Recall ≈ 95%	Explain ability and early diagnosis were not addressed
[37]	Field Rice Leaf Dataset (complex background)	Lightweight generalized DL framework	Accuracy ≈ 94–96%; Sensitivity ≈ 93%	Early-stage disease detection remained difficult
[38]	Multi-condition Rice Leaf Dataset	ML + DL ensemble	Accuracy ≈ 97%; F1 ≈ 0.96; AUC ≈ 0.98	High complexity limits real-time deployment

PROBLEM STATEMENT

Diagnosing rice plant diseases on time and accurately is still a major issue for farmers. Although CNN-based deep learning models have enhanced the capability of automated disease classification, their capabilities are generally restricted by low robustness, poor generalization, noise sensitivity, and insufficient early-stage disease detection. Current models are also challenged by small and imbalanced datasets, and there is a lack of thorough cross-dataset validation. In this regard, to address these issues, this work proposes a hybrid deep learning model-based approach for early-stage detection and classification of rice plant diseases.

RESEARCH OBJECTIVES

Based on the literature survey, below are the following research gaps which authors have been identified and framed as research objectives:

RO1: To design an efficient deep learning model for early detection of rice plant disease.

RO2: To develop hybrid deep learning models for automated feature extraction and classification of rice plant disease types.

RO3: To evaluate the proposed model on benchmark dataset and compare results with existing state-of-the-art methods.

RO4: To integrate large dataset and real time data analysis for improved diagnostic performance.

PROPOSED METHODOLOGY

The overall sequence of the proposed research is shown in Figure 15. The process carried out for the rice leaf disease detection consists of four stages, first stage is selection of dataset, the second stage is data preprocessing and augmentation, the third stage is data analysis and in forth stage model is evaluated based on standard performance metrics.

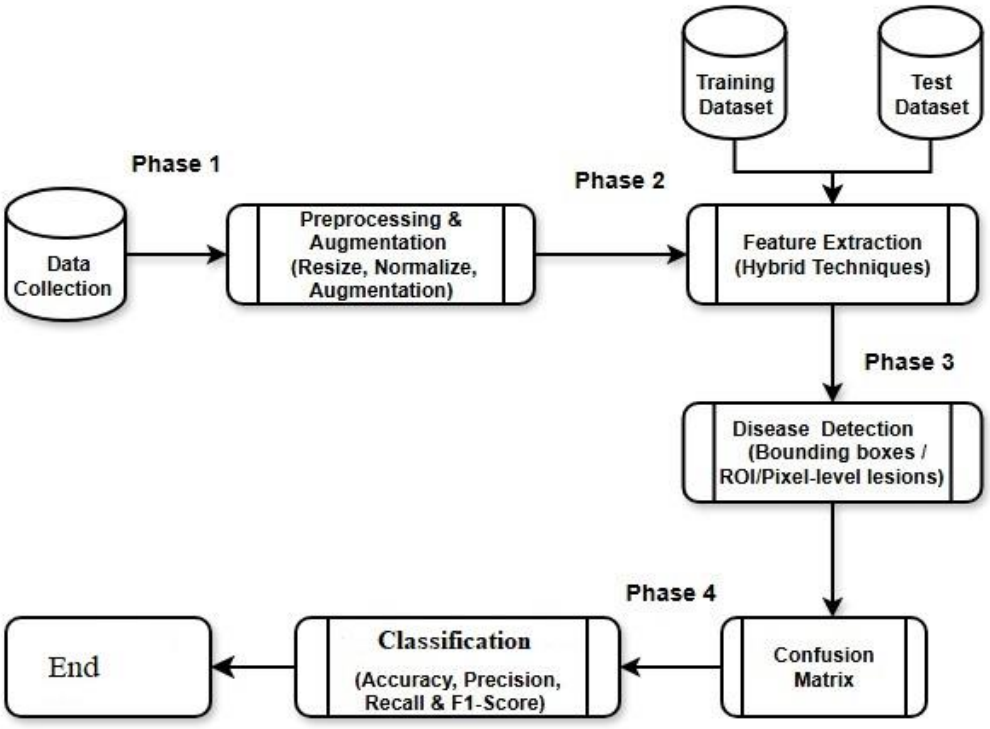


Figure 15: Proposed Model Flow Chart

This research uses dataset which are obtained from open repositories as mentioned below.

- **Dataset No.1** Rice Diseases Image Dataset (https://doi.org/10.34740/kaggle/dsv/796736)

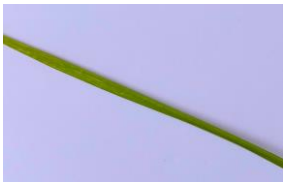
This dataset comprises rice plant disease images, often used as a foundational dataset for research on rice plant diseases, specifically Brown Spot, Hispa, Leaf Blast, and Healthy. All images in this database are taken in a laboratory setting. Currently, the dataset contains 3345 rice leaf images with 4 diseases types. It is a large and annotated dataset for the identification of rice diseases. It consists of RGB images of rice leaves collected from actual rice paddies with the following details as shown in Table 2. Table 3 represents the images from dataset with all the four diseases types.

Table 2: Dataset Description

Attribute	Details
Dataset Title	Rice Diseases Image Dataset
DOI	10.34740/KAGGLE/DSV/796736
Creator / Author	Huy Minh Do
Data Type	RGB rice leaf images
Number of Classes	4
Classes	Brown Spot, Hispa, Leaf Blast, Healthy
Total Images	5447
Image Resolution	Variable (commonly resized to 224×224 for training)
Usage	Rice leaf disease classification using deep learning
Dataset Category	Plant disease image classification

Table 3. Sample images from Rice Diseases Image Dataset with labels and descriptions

Image	Label	Description
	Brownspot	Brown spot disease lesion is visible across the leaf surface

	Hispa	Leaf surface scraped and damaged by hispa feeding
	LeafBlast	Blast disease lesions with light and dark patches
	Healthy	No signs of disease, typical green leaf

- **Dataset No.2 (**https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases**)**

The dataset of Rice Leaf Disease is taken from the UCI Machine Learning Repository and contains 120 labeled rice leaf images covering three diseases: bacterial leaf blight, brown spot, and leaf smut. Each class has 40 images captured under natural light on a plain background, making the dataset suitable for rice plant disease classification tasks. Table 4 represents description of dataset 2 which authors utilize to implement the proposed model.

Table 4. Description of Rice Leaf Diseases Dataset (UCI Machine Learning Repository)

Dataset Name	Source	Disease Classes	Description
Rice Leaf Diseases Dataset	UCI Machine Learning Repository	Brown Spot, Leaf Blast, Hispa	Contains images of rice leaves affected by Brown Spot, Leaf Blast, and Hispa diseases. The dataset is commonly used for

			evaluating image-based classification models in precision agriculture.

Pre-processing Data (Phase 1): In rice disease detection systems, preprocessing is carried out by standardizing image dimensions, suppressing noise, isolating leaf regions, and enhancing visual features to minimize the impact of background clutter and uneven lighting conditions. Thereafter, to strengthen deep learning models, synthetic image diversity is introduced through augmentation operations such as geometric transformations, intensity variations, enabling better learning from limited and imbalanced rice disease datasets. To prepare data before processing and using it in the classification process.

Feature Extraction (Phase 2): In this Phase, Convolutional layers extract the features (low to high level features).

Detection of Diseases (Phase 3): Detection, which involves drawing a bounding box around an object of interest (ROI using R-CNN/Fast RCNN/ Faster RCNN) in a rice leaf image, while it is also possible to find several objects of interest in the same image. Thereafter, identifies diseased regions in rice leaf images by learning discriminative spatial and texture features using networks. In this step, testing is carried out to test all training data using the designed network structure.

Classification and Evaluation (Phase 4): In this step, data is collected regarding the results of the experiments that have been carried out, with the aim of seeing the results and evaluating how successful the method is. Evaluating the performance of a classifier is an essential task in the field of deep learning. In this section, authors utilize different standard performance metrics.

In a multiclass system, to quantify the behavior of classifiers in each class, author divided confusion matrix into regions. Figure 16 represents that confusion matrix is divided into four regions of interest:

Performance Evaluation:

The proposed work will be evaluated with the help of standard performance metrics. The Figure 16 represents all the possible outcome of the models.

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Figure 16: Confusion Matrix

Accuracy (ACC) denotes the proportion of correct predictions that algorithm has made compared to total number of samples. It can also be understood as the fraction of correct predictions compared to the total number of samples as represented in Equation 4. To perform better on imbalanced data sets, balanced accuracy can be used [44].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (4)$$

- **Precision**

It can be defined as the sample predicted as positive are actually positive. It is most widely used assessment metric for checking the quality of deep learning algorithms. The Equation 5 can be utilized to find the value of precision [44].

$$Precision = \frac{TP}{TP + FP} \qquad (5)$$

- **Recall**

It is defined as the total number of actual positive samples which were accurately predicted by the model. Its objective is to find the total number of positive cases. Equation 6 can be utilized to calculate the quantity of Recall metric [44].

$$Recall = \frac{TP}{TP + FN} \qquad (6)$$

- **F1-Score**

F1-Score can be used for the assessment of deep learning models. It the harmonic mean of precision and recall. Equation 7 helps in finding the value of F1-score [44].

$$F1 - Score = \frac{Precision * Recall}{Precision + Recall} \qquad (7)$$

EXPECTED OUTCOME OF THE RESEARCH

- The design of an effective hybrid DL model for early detection of rice plant disease.
- Improving the classification performance of the evaluation parameters for differentiating between types of rice plant diseases especially in early stages of the disease.
- Designing of hybrid deep learning models that performs better than unique deep learning models.
- Validating the hybrid DL model on the existing datasets by comparing the model with the existing state of the art approaches.
- Improving the interpretability of the model through feature engineering, transformers and attention-based mechanisms.

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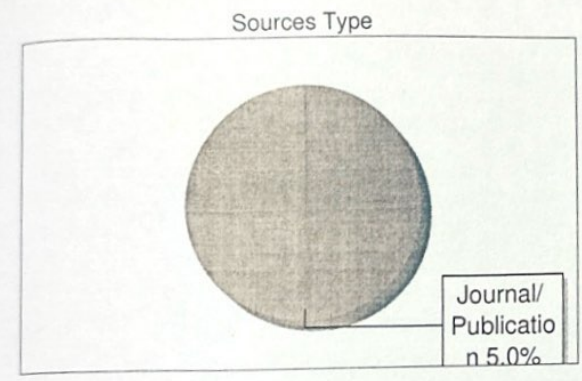

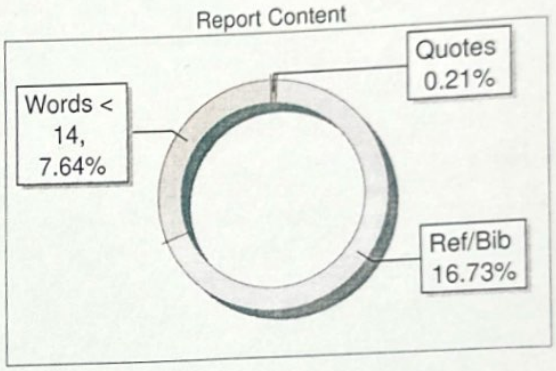

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Early Detection and Classification of Rice Disease using Hybrid Deep Learning Technique

SHORT SYNOPSIS

by

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ABSTRACT

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Productivity in rice is impacted by various and highly contagious diseases, resulting in a significant loss of yield. Conventional methods for rice leaf disease detection and classification are based on human expert evaluation, which is prone to human error and variability based on the evaluator's experience, growth stage of the rice plant, and environmental factors. Although recent developments in machine learning and deep learning, especially CNN-based models, have improved the accuracy of automated disease classification, the lack of adoption of advanced models like Faster R-CNN and vision transformers has hampered classification accuracy, often resulting in a higher rate of misclassification.

To address these challenges, this study proposes a hybrid deep learning model that integrates CNN-based feature extraction/RCNN/fast CNN, attention mechanism and transformer models for early and accurate rice disease classification. The proposed method is expected to improve the accuracy of classification and minimize the rate of false classification. The performance of the proposed model will be assessed using accuracy, precision, recall, F1-score and other standard metrics.

Keywords: Rice Disease, Computer Vision, Deep Learning (DL), Machine Learning (ML), Convolutional Neural Networks, Attention Mechanism, Transformers.

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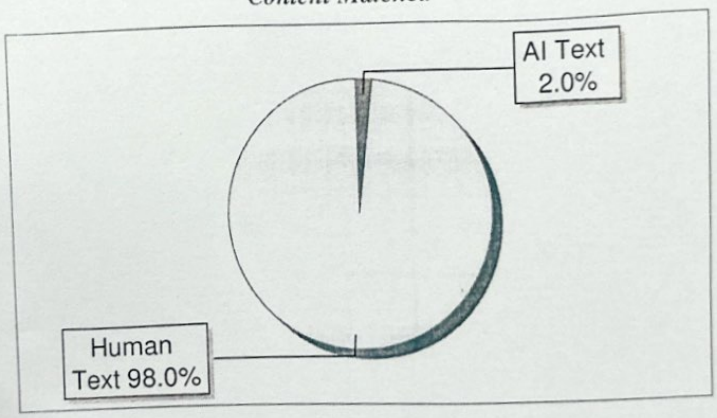

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